

AN EXPLAINABLE AI FRAMEWORK FOR AUTOMATED CREDIT RISK ADVISORY USING MACHINE LEARNING: A CASE STUDY IN THE UGANDAN FINANCIAL SECTOR

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CHAPTER ONE

INTRODUCTION

1.1 Research Background

Artificial Intelligence (AI) is revolutionizing the financial sector by enabling faster, more accurate, by enabling cost-efficient, data-driven decision-making processes. Financial institutions increasing in AI technologies in credit scoring, fraud detection, customer segmentation, and risk assessment (Arner, Barberis, & Buckley, 2017;

Khandani, Kim, & Lo, 2010). According to PwC (2023), 45% of global financial institutions have already integrated Explainable AI (XAI) tools into their systems to promote transparency, build stakeholder trust, and ensure regulatory compliance. However, the adoption and effectiveness of AI technologies remain uneven, particularly in developing economies with underdeveloped digital infrastructures (World Bank, 2022; OECD, 2021).

One of the most significant barriers to the adoption of AI in finance is the opacity of many machine learning models, commonly referred to as the “black-box” problem. This is particularly problematic in high-stakes sectors like finance because decisions such as loan approvals, credit risk assessments, and fraud detection directly impact individuals' financial well-being and institutional accountability. Without clear explanations for these decisions, it becomes difficult to ensure fairness, detect errors, or comply with regulatory standards. Complex models such as deep neural networks and ensemble techniques often provide limited interpretability which obstructs human understanding and oversight (Doshi-Velez & Kim, 2017; Guidotti et al., 2018). This lack of transparency undermines trust, raises ethical concerns, and complicates efforts to meet compliance standards in high-stakes decision domain.

Notably, global financial institutions have collectively incurred over \$5 billion in fines in recent years due to failures in algorithmic transparency and accountability (Smith et al., 2022). For instance, in 2020, the U.S. bank Wells Fargo faced regulatory scrutiny over its opaque automated systems that led to unfair loan denials highlighting the real-

world consequences of black-box models. While such cases are more documented in developed economies, similar risks loom in Sub-Saharan Africa, where weak regulatory oversight and limited technical capacity could exacerbate the consequences of algorithmic bias and misjudgement.

In financial services, AI enhances credit decisioning, risk profiling, and fraud mitigation by augmenting human judgment with data-driven insights. These applications align with broader goals of sustainable development (Malik, Muhammad, & Waheed, 2024). To bridge the interpretability gap, a range of explainable AI methods has emerged. Model-agnostic techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) offer insights into model predictions without compromising performance (Lundberg & Lee, 2017; Ribeiro, Singh, & Guestrin, 2016). Additionally, inherently interpretable models such as decision trees and logistic regression remain valuable in domains requiring clarity, traceability, and stakeholder validation (Molnar, 2022).

A qualitative interview with a senior manager at Stanbic Bank Uganda provided valuable insight into challenges faced by financial institution in the region. While the bank has implemented AI-based tools for credit scoring and transaction monitoring, several persistent barriers hinder optimal implementation. These include poor data infrastructure, high dependency on manual data entry, and issues related to data corruption and incompleteness. Such challenges compromise the reliability of machine learning models and introduce significant ethical, operational, and compliance risks (Munoko, Brown-Liburd, & Vasarhelyi, 2020). Consequently, there

is a pressing need for robust data governance and the integration of explain ability to support responsible AI adoption. Furthermore, the trade-off between model performance and interpretability remains a critical concern. As advanced models grow in complexity, their outputs become increasingly difficult for non-technical stakeholders to interpret and trust (Carvalho, Pereira, & Cardoso, 2019). Without effective explanation tools and stakeholder training, even highly accurate AI systems risk being underutilized, misapplied, or outright rejected. This situation underscores the urgent need for human-centric XAI frameworks that prioritize stakeholder understanding and regulatory compliance especially in emerging financial ecosystems such as Uganda's (Hanif, 2021; Tolan et al., 2019).

1.2 Problem Statement

Artificial Intelligence (AI) is transforming the financial services industry by enhancing core functions such as credit evaluation, fraud detection, and risk analysis. These AI-driven system enable faster, data-drive decision-making and operational efficiency. However, in low-resource settings such as Uganda, the integration of AI remains fraught with challenges including technical limitations, ethical concern, and regulatory constraints (Barocas et al., 2019; Crisanto et al., 2024).

Among the most critical challenges is algorithmic bias, often rooted in historical data that reflect systemic inequalities. These biases can lead to discriminatory outcomes in credit scoring and loan approvals, particularly when AI models function as opaque "black-boxes" that lack transparency (Mehrabi et al., 2021; Doshi-Velez & Kim, 2017). The inability of financial stakeholders to interpret, audit, or challenge AI decisions erodes institutional trust and complicates compliance with financial regulations. Local insights from Stanbic Bank Uganda further illustrate these challenges manifest in practice. Although the bank has adopted AI tools for credit scoring and transaction monitoring it faces significant implementation barriers. Fragmented data systems, reliance on manual record-keeping, and occasional data manipulation compromise the integrity and accuracy of model outputs. These conditions severely undermine institutional confidence in AI-driven systems and highlight the need for improved data governance and system transparency. (add citation here)

In addition, the heavy dependence on sensitive customer data raises serious concerns regarding privacy and cybersecurity. In regions with underdeveloped legal frameworks and limited enforcement capabilities, the risk of breaching international privacy standard such as General Data Protection Regulation (GDPR) is significantly heightened (Zhang et al., 2023). These risks further complicate AI adoption in emerging economies, where regulatory mechanisms are still evolving. (add citation here)

Despite the growing adoption of AI in global financial services, there is limited research and practical implementation of explainable AI solutions tailored to low-

resource environments such as in Sub-Saharan Africa. These gaps underscore the urgent need for a context-aware, explainable AI framework, supported by practical evaluation, that enhances model transparency, improves stakeholder trust, and facilitates regulatory alignment in credit scoring systems within emerging financial ecosystems. (Maple et al., 2023).

1.3 Objectives

Primary Objective:

To design and evaluate a context-aware, explainable AI framework that improves transparency, fairness, and regulatory compliance in credit scoring systems within data-constrained financial institutions (Carvalho, Pereira, & Cardoso, 2019; Maple et al., 2023).

Specific Objectives:

1. To examine the impact of data quality and infrastructure on the performance and fairness of AI models in credit scoring.
2. To investigate suitable Explainable AI (XAI) techniques that improve model interpretability and decision accountability in data-constrained financial environments.
3. To assess the applicability and effectiveness of XAI methods (e.g., SHAP, LIME) in supporting transparent credit scoring under resource-limited financial infrastructures.

1.4 Research Questions

1. How do poor data practices such as manual entry, incomplete records, and data corruption affect the performance and fairness of AI models in financial institutions?
2. What practical approaches and techniques can be used to implement Explainable AI in financial institutions operating with limited or low-quality data?
3. Which XAI methods are most effective in enhancing interpretability, fairness, and stakeholder trust in AI-powered credit scoring within low-resource environments?
4. To what extent can XAI tools (e.g., SHAP, decision tree visualizations) promote ethical, transparent, and compliant decision-making in credit risk assessments?

1.5 Scope and Research Gaps

Scope:

This study focuses on the design and evaluation of an Explainable Artificial Intelligence (XAI) framework tailored for AI-based credit scoring within data-constrained financial institutions, using Stanbic Bank Uganda as a case study. The research is confined to credit scoring systems and does not extend to fraud detection or broader risk assessment domains.

It investigates how poor data quality, manual record-keeping, and fragmented data infrastructures affect the performance, fairness, and interpretability of AI models in

these environments (Munoko, Brown-Liburd, & Vasarhelyi, 2020; Mehrabi et al., 2021).

The study further explores the operationalization of model-agnostic XAI techniques specifically SHAP and LIME to improve model transparency, regulatory alignment, and stakeholder trust (Lundberg & Lee, 2017; Ribeiro, Singh, & Guestrin, 2016).

The evaluation includes both technical assessments (e.g., model accuracy vs. explainability trade-offs) and qualitative feedback from key financial stakeholders such as loan officers and data managers. The expected outcome is a context-sensitive, stakeholder-informed XAI framework that can be realistically implemented in low-resource financial environments (Hanif, 2021; Molnar, 2022).

Research Gaps

1. Contextual Gaps

While AI is being increasingly adopted in global financial services, limited empirical research exists on its implementation within financial institutions in low-resource settings such as Sub-Saharan Africa. These regions face unique challenges including fragmented infrastructure, informal financial ecosystems, and limited technical expertise that are often overlooked in mainstream AI research (World Bank, 2022; Maple et al., 2023; Hanif, 2021).

2. Integration Gaps

Most existing studies on Explainable AI (XAI) remain conceptual, focusing on theoretical frameworks rather than integrated technical solutions suitable for real-world deployment. This gap hinders the translation of academic findings into functional systems for financial institutions in data-constrained environments (Molnar, 2022; Doshi-Velez & Kim, 2017).

3. Data Integrity

The effects of manual data entry, incomplete records, and occasional data manipulation on the fairness and accuracy of AI models remain underexplored. These practices are prevalent in developing financial institutions and present significant risks to model performance and ethical decision-making (Munoko, Brown-Liburd, & Vasarhelyi, 2020; Mehrabi et al., 2021).

4. Regulatory Relevance

Existing AI regulatory frameworks such as the General Data Protection Regulation (GDPR) and the EU AI Act may not be fully applicable or enforceable in developing economies. There is a need for localized regulatory approaches that are informed by, and supported through, explainable AI methods to ensure compliance and accountability in less-regulated financial systems (Zhang et al., 2023; Crisanto et al., 2024).

5. Stakeholder Usability

XAI research often overlooks the practical needs of key end-users including loan officers, compliance managers, and regulators who must interpret, validate, and act upon AI-driven decisions. In low-resource settings, where digital literacy may vary, explainability must go beyond algorithmic transparency to deliver intuitive, actionable insights. Addressing this usability gap is essential for fostering trust, increasing system adoption, and ensuring ethical outcomes (Tolan et al., 2019; Hanif, 2021).

1.6 Contributions of the Study

This study contributes to both academic discourse and practical innovation in the fields of Artificial Intelligence (AI), Explainable AI (XAI), and financial technology, especially in the context of low-resource financial ecosystems.

1. Contextual Contribution

By focusing on Stanbic Bank Uganda as a case study, this research provides empirical insights into the implementation challenges and opportunities of AI and XAI in Sub-Saharan Africa. It addresses the underrepresentation of low-resource financial institutions in global AI literature (Barocas et al., 2019;

Maple et al., 2023) and highlights region-specific constraints such as data fragmentation, infrastructural limitations, and compliance gaps (World Bank, 2022; Munoko, Brown-Liburd, & Vasarhelyi, 2020).

2. Technical Contribution

The study proposes a conceptual software framework designed to centralize and enhance financial data quality while integrating model-agnostic XAI tools such as SHAP and LIME. This solution bridges the gap between model performance and interpretability (Lundberg & Lee, 2017; Ribeiro, Singh, & Guestrin, 2016), offering a practical pathway for deploying explainable AI in institutions with limited data infrastructure (Molnar, 2022).

3. Regulatory and Ethical Alignment

Through its examination of explainability in environments with weak regulatory enforcement and ethical oversight, the study contributes to the formulation of localized, context-aware AI governance models. These findings can inform future regulatory strategies in emerging economies, ensuring AI systems are transparent, fair, and legally compliant (Crisanto et al., 2024; Zhang et al., 2023).

4. Stakeholder-Centric Design and Usability

The research incorporates feedback from key stakeholders including loan

officers, data managers, and regulators to assess the usability and interpretability of the proposed XAI framework. By emphasizing human-centered design and explainability, it promotes practical adoption and fosters trust among both technical and non-technical users (Tolan et al., 2019; Hanif, 2021).

5. Strategic Guidance for Financial Institutions

The study provides actionable recommendations for financial institutions in low-resource environments on how to implement explainable, data-aware AI solutions. It emphasizes the role of transparency, accountability, and stakeholder communication as foundational pillars for sustainable and ethical AI-driven credit risk management (Malik, Muhammad, & Waheed, 2024; Carvalho, Pereira, & Cardoso, 2019).

CHAPTER TWO

Chapter 2: Literature Review

2.1 Introduction

This chapter provides a comprehensive literature review related to the adoption and explain ability of Artificial Intelligence (AI) in financial services, particularly in low-resource environments. It outlines the role of AI in credit scoring, addresses data quality challenges, evaluates algorithmic fairness, and discusses regulatory and ethical considerations. Particular focus is placed on Explainable AI (XAI) in Sub-Saharan Africa to align with this study's research objectives. The review highlights themes

such as stakeholder trust, data infrastructure limitations, algorithmic accountability, and the usability of XAI systems. The findings also form the foundation for the conceptual framework and research methodology.

2.2 AI in Financial Services

2.2.1 AI and Data Quality Limitations in Low-Resource Financial Institutions

AI models depend on high-quality, structured data to function effectively. Institutions in low resource settings such as Uganda are prone to systemic issues such as manual data input, fragmented records, and inaccurate or inconsistent datasets (Barocas et al., 2019; Munoko et al., 2020). For instance, Stanbic Bank Uganda continues to employ legacy systems that contain human input, which exposes it to input errors, duplication, and prejudice.

Hanif (2021) and Carvalho et al. (2019) argue that for such "dirty data," even the most sophisticated AI models will act sub-optimally and yield unfair or biased outcomes. Further, as opposed to banks in developed countries, Ugandan banks lack strong data governance systems, which contribute to these problems.

Primary Insight is that most current research makes available clean, digitized data, a premise on which it does not rest in the case of Uganda.

While these data challenges are widely acknowledged, few studies contrast Uganda's situation with other developing economies like Kenya, Nigeria, or India. For instance, India's adoption of Aadhaar-based digital identity systems has significantly improved data quality in lending. In contrast, Uganda's fragmented ID systems and inconsistent record-keeping continue to hinder effective AI adoption. This comparative context strengthens the rationale for a Uganda-focused framework.

2.2.2 Usability and Human Interaction with XAI

While technical interpretability is well-studied, the usability and human-centered interaction with XAI tools remain underexplored, particularly in Sub-Saharan Africa. Few studies have investigated how non-technical stakeholders perceive, understand, or utilize outputs from tools like SHAP or LIME. Yet, usability is central to the practical effectiveness of XAI in real-world financial environments.

For example, Hussain et al. (2022) emphasize that visual complexity and cognitive overload often make even the most accurate explanations inaccessible to frontline users. In Uganda, loan officers and branch managers frequently lack the data science

training needed to interpret SHAP summary plots or LIME's local surrogate models. This gap in human-computer interaction reduces trust and adoption. Addressing usability concerns involves simplifying explanation interfaces, integrating human-centered design, and offering training to stakeholders. Comparative case studies in Kenya and India show that when end-users are involved early in the development of AI tools, adoption improves significantly (Sabharwal et al., 2024). This study seeks to fill this usability gap by evaluating how understandable and actionable current XAI tools are for diverse stakeholder groups in Uganda's financial sector.

2.2.3 Applications of AI in Credit Scoring

AI applications in credit scoring have become essential in modern banking, leveraging non-traditional datasets such as social media activity, mobile money transactions, and customer purchasing behaviour. These tools outperform traditional statistical models in predicting creditworthiness, especially in markets with limited formal financial

history. Bhatnagar & Mahant (2024) noted that these innovations help expand access to credit for underserved populations while improving institutional efficiency.

2.2.4 Benefits and Challenges of AI Adoption in Financial Institutions

AI offers several advantages, such as automating repetitive tasks, enhancing fraud detection, personalizing customer services, and enabling real-time risk assessment (Das & Rad, 2020). However, the implementation is not without hurdles. Institutions face high initial investment costs, a shortage of skilled personnel, and challenges related to the interpretability of complex algorithms. In developing regions, infrastructural limitations often delay or prevent AI integration (Mehrabi et al., 2021).

2.3 Data Challenges in Low-Resource Financial Environments

2.3.1 Data Quality and Infrastructure Limitations

Financial institutions in Sub-Saharan Africa often rely on manual data collection processes, which can lead to incomplete or inconsistent records. Hanif (2021) emphasized that poor data quality undermines the performance of machine learning

models, leading to inaccurate predictions. Inadequate digital infrastructure, paper-based systems, and weak data validation mechanisms all contribute to unreliable inputs.

2.3.2 Impact of Data Practices on AI Model Performance and Fairness

Low-quality data not only reduces predictive accuracy but also perpetuates social biases present in historical records. According to Barocas et al. (2019), biased training data leads to discriminatory outcomes, disproportionately affecting vulnerable groups. Carvalho et al. (2019) argue that the presence of noise and missing data skews model performance and confidence, especially when applying AI in credit scoring. This issue directly aligns with Objective 1 of this study, which seeks to understand the data-centric barriers to trustworthy AI adoption in Uganda.

2.4 Algorithmic Bias and Fairness in Credit Scoring

2.4.1 Sources of Bias in Credit Data

Historical and systemic discrimination embedded within legacy financial systems is often inherited by AI models trained on such data. Mehrabi et al. (2021) identified

various sources of algorithmic bias, including class imbalance, underrepresentation of minorities, and proxy variables that reflect sensitive attributes.

2.4.2 Fairness Metrics and Mitigation Approaches

Efforts to mitigate algorithmic bias in credit scoring include techniques like data rebalancing, adversarial debiasing, and imposing fairness constraints during training. While promising, these methods require technical expertise and rigorous validation. The application of fairness-aware AI remains limited in Sub-Saharan Africa, partly due to infrastructural and capacity constraints.

2.5 Explainable AI (XAI) in Financial Decision-Making

2.5.1 Overview of XAI: Definitions and Importance

Explainable AI refers to methods and techniques that make the output of machine learning models understandable to humans. Doshi-Velez & Kim (2017) assert that interpretability is critical for high-stakes domains such as finance, where transparency impacts stakeholder trust and legal accountability.

2.5.2 Common XAI Techniques (e.g., SHAP, LIME, Decision Trees)

SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are widely used post-hoc tools that help unpack model decisions by attributing importance to input features. Guidotti et al. (2018) and Hussain

et al. (2022) discuss the role of these tools in enhancing confidence among end-users, auditors, and regulators.

2.5.3 Operationalizing XAI in Data-Constrained Environments

In an effort to balance the black-box characteristics of AI systems, methods such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) have gained popularity (Doshi-Velez & Kim, 2017; Guidotti et al., 2018). These instruments aim to render paths of decisions in AI outputs more transparent, especially in credit scoring and fraud detection. Hussain et al. (2022) and Sabharwal et al. (2024) propose the use of SHAP in the financial sector to increase stakeholder understanding and institutional transparency.

But this requires adequate digital literacy and technical infrastructure, both of which are lacking in Ugandan banks. This paper examines the feasibility of using explain ability tools like SHAP and LIME in such an environment.

In contexts with low digital literacy and limited computational resources, deploying XAI requires simplified user interfaces and lightweight algorithms. Graphical dashboards, color-coded explanations, and pre-interpreted decision trees may serve as viable alternatives. This aligns with Objective 2 of the study, which seeks to identify usable XAI strategies in Uganda's financial sector.

2.6 Regulatory Compliance and Ethical Considerations

2.6.1 AI Regulations Relevant to Financial Services (e.g., GDPR, EU AI Act)

Global regulatory frameworks like the General Data Protection Regulation (GDPR) and the proposed EU AI Act outline standards for transparency, fairness, and data

governance in automated systems (Fernández, 2019). These serve as benchmarks for responsible AI deployment worldwide.

2.6.2 Challenges for Regulatory Alignment in Developing Economies

Ethical deployment of AI in finance requires both institutional accountability and regulatory oversight. Advanced economies are beholden to the imposition of transparent guidelines such as the EU's General Data Protection Regulation (GDPR) and the AI Act. Uganda's regulatory framework is, however, deficient in this aspect. Fernández (2019) warns of "governance vacuums," which are present whenever AI systems are implemented without clear mechanisms of accountability.

At Stanbic Bank Uganda, for example, data privacy regimes are yet to be developed , and there are few industry-wide standards for transparency or fairness in algorithms. As Mehrabi et al. (2021) note, models can reinforce systemic biases if deployed without localized ethics protection.

Despite these standards, many African countries lack local AI regulations. Zhang et al. (2023) highlight the governance vacuum, where systems are adopted without oversight, increasing the risk of privacy breaches and discrimination. Institutional weaknesses and lack of regulatory clarity exacerbate these risks.

2.7 Gaps in Literature

2.7.1 Contextual Gaps in Sub-Saharan Africa

Most AI literature originates from high-income settings with robust infrastructure, making them less applicable to low-resource environments. As Munoko et al. (2020) point out, there is minimal research on how socio-technical challenges in Africa affect AI performance and outcomes.

2.7.2 Technical and Integration Gaps in XAI Deployment

Although tools like SHAP and LIME have shown promise, few studies have tested their effectiveness in environments with low technical capacity or limited computing power. Sabharwal et al. (2024) call for empirical evaluations of XAI in African financial institutions.

2.7.3 Stakeholder Usability and Trust in XAI Systems

There is a dearth of literature on how different stakeholders interpret and respond to AI explanations over time. Bhatnagar & Mahant (2024) stress that trust is not solely dependent on technical accuracy but also on clarity, accessibility, and user experience.

Trust is a critical enabler for AI adoption. According to Bhatnagar & Mahant (2024), stakeholders including customers, regulators, and internal staff are more likely to accept AI-generated decisions if they can understand the reasoning behind them. However, most AI tools currently in use (especially those relying on machine learning) offer little to no explainability.

Sabharwal et al. (2024) stress that trust is not only technical but also emotional users must feel they are treated fairly. In Uganda, customer resistance to automated loan decisions stems from a lack of clarity on how those decisions are reached. This study investigates how embedding XAI features can enhance trust and acceptance across different user groups.

2.7.4 Bank Process Limitations in Uganda

Ugandan banks face multiple operational inefficiencies that directly impact AI implementation. Many customer facing operations, including credit application, KYC verification, and fraud tracking, are semi-manual and lack integration across departments (Munoko et al., 2020). These limitations delay data availability and reduce the timeliness of AI-powered insights.

Furthermore, training staff to work with AI tools is a slow process. Limited technical capacity and financial constraints often prevent banks from adopting cutting edge systems. For example, while JPMorgan Chase uses AI to detect fraud anomalies in seconds, Stanbic Bank still conducts many fraud investigations manually. These delays reduce the return on AI investment and make real-time analytics difficult.

Implication: AI systems cannot operate effectively without optimized backend processes, automation, and skilled human oversight.

2.7 Comparative Case Study: JPMorgan Chase vs Uganda

JPMorgan Chase is often cited as a leader in ethical AI implementation, using tools like fairness-aware algorithms, robust evaluation systems, and anomaly detection technologies (KPMG, 2020; JPMorgan Chase, 2021). Their operations are backed by mature governance frameworks and advanced digital infrastructure.

In contrast, Ugandan banks operate with limited infrastructure and no standardized AI governance policies. The comparison highlights how success in high resource settings cannot be replicated in developing countries without significant adaptation. This study seeks to develop a localized, centralized XAI solution that addresses these structural gaps.

2.8 Conceptual Framework

This study proposes a conceptual framework integrating key themes: AI applications in finance, data infrastructure limitations, ethical and regulatory concerns, and stakeholder trust. At its core, the framework suggests that the successful deployment of XAI depends on:

- Quality and inclusiveness of training data
- Alignment with local ethical standards and regulations
- Usability of XAI outputs for diverse stakeholders
- Availability of technical infrastructure This model guides the research methodology and informs the evaluation metrics for XAI systems in Uganda.

2.9 Summary

This chapter reviewed the role of AI in financial services, focusing on issues such as data quality, algorithmic bias, explain ability, and regulatory compliance. Gaps in the literature highlight the need for localized research and practical XAI solutions tailored to Sub-Saharan Africa. These insights provide the basis for the study's conceptual framework and help guide the development of ethical, transparent, and effective AI systems in low-resource environments.

The reviewed literature emphasizes the transformative potential of AI in finance but also uncovers significant gaps in transparency, fairness, and regulatory readiness, especially in resource-constrained settings. These insights directly inform the conceptual framework, which aims to propose a centralized XAI solution tailored for institutions like Stanbic Bank Uganda.

Thematic Area	Identified Gap
Data Quality & Bias	Limited research on the effect of poor infrastructure on AI performance and fairness
Bank Processes	Lack of automation and integration undermines AI utility
XAI Techniques	Little work applying SHAP/LIME in low-literacy, resource-constrained environments
Governance & Regulation	Scarcity of localized AI governance frameworks in Sub-Saharan Africa
Stakeholder Trust	Limited insight into the long-term effect of explainability on customer perception
AI Implementation Readiness	No standardized models for deploying AI in fragile financial ecosystems

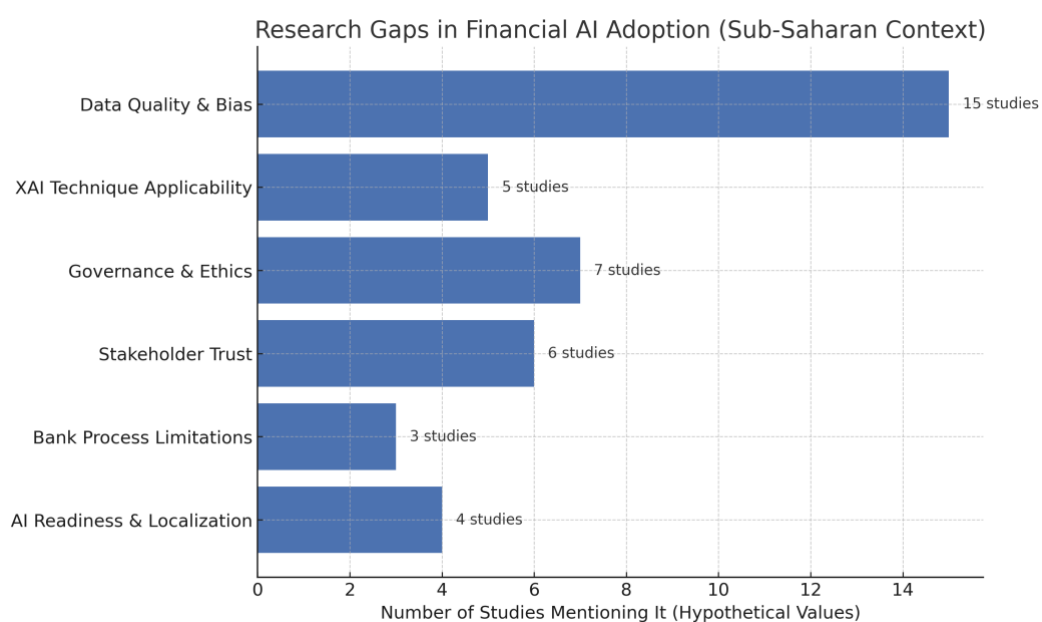


Figure 2.1 Summary of Key Research Gaps in Financial AI Adoption in Sub-Saharan Africa (Hypothetical Data)

Figure 2.1 provides a visual representation of the research gaps discussed. The hypothetical data reflects the relative emphasis found in the reviewed literature, highlighting that while data quality and bias are widely addressed, there is significantly less attention to bank process limitations and implementation readiness in low-resource settings like Uganda.

Chapter 3: Methodology

3.1 Introduction

This chapter outlines the research methodology employed in this study, which investigates the implementation of Explainable Artificial Intelligence (XAI) in financial services within low-resource environments, with a focus on Uganda. The methodology is structured to achieve the research objectives defined in Chapter 1, specifically addressing the challenges posed by data quality, algorithmic transparency, and stakeholder trust in AI systems. The chapter provides a comprehensive explanation of the research design, data collection methods, instruments used, sampling techniques, and ethical considerations.

A methodological approach is critical in ensuring the validity and reliability of findings, particularly when studying complex and emerging technologies such as AI in the financial sector. As the research explores both technological and human-centric dimensions of XAI, a combined approach was necessary to capture the multifaceted nature of the phenomena. Furthermore, the methodology aligns with the conceptual framework discussed in Chapter 2, incorporating components such as data quality, regulatory environment, and stakeholder trust.

The study is designed to be both exploratory and explanatory. Exploratory elements aim to uncover how institutions in Uganda perceive and interact with AI systems, especially in terms of explain ability and trust. Explanatory aspects seek to identify patterns or relationships between data quality, AI model performance, and

stakeholder satisfaction. Therefore, the methodology must be sufficiently flexible yet structured to capture both qualitative and quantitative evidence.

The methodology also considers contextual constraints present in Sub-Saharan African financial institutions, such as limited access to high-quality datasets, varying levels of digital maturity, and a lack of uniform regulatory enforcement. These realities necessitate methodological pragmatism, where field conditions determine the feasibility of ideal research techniques. Accordingly, adjustments were made to suit local capacities and institutional access.

Finally, this chapter justifies the selection of the research design and explains the rationale behind data collection methods. Both qualitative and quantitative data were collected through interviews and secondary datasets to provide a well-rounded understanding of XAI's implementation in Uganda. The triangulation of methods enhances the credibility of findings and supports a robust analysis of AI system deployment within the constraints of developing financial environments (Creswell & Plano Clark, 2018).

3.2 Research Design

This study uses a qualitative case study approach to explore the integration and impact of Explainable AI (XAI) in financial institutions, particularly Stanbic Bank Uganda. The procedures involve semi-structured interviews, document review, and thematic analysis, aimed at understanding stakeholder experiences, institutional challenges, and implementation outcomes.

This design is particularly suitable for this research because it allows for the integration of contextual stakeholder perceptions with objective performance data on credit scoring algorithms.

The **qualitative component** focuses on gathering expert insights through semi-structured interviews with bank personnel, data officers, regulators, and IT managers. These interviews are intended to understand stakeholder views on explain ability, trust, data limitations, and regulatory preparedness. The qualitative phase helps uncover phenomena that may not be captured through statistical data alone and contributes to theory development in a novel research context (Silverman, 2016).

By employing a **design science paradigm**, the research aims not only to understand but also to propose a contextually relevant XAI framework for low-resource financial institutions. This practical orientation reflects the study's applied nature and its goal of addressing real world challenges through actionable insights. Design science emphasizes artifact creation in this case, a conceptual framework grounded in empirical evidence and refined through iterative analysis (Hevner et al., 2004).

Overall, the qualitative methods approach enables a holistic investigation by integrating the human, technological, and organizational aspects of AI implementation. It also mitigates the limitations of single-method studies, which may either lack depth or overlook general patterns. The integration of qualitative richness is essential for building a well-rounded argument regarding XAI deployment in resource constrained environments.

3.2.1 Overall Research Approach

The overarching research approach aligns with the **Design Science Research Methodology (DSRM)**, which seeks to produce innovative solutions (or artifacts) to practical problems through rigorous inquiry. DSRM is particularly appropriate when the objective is both explanatory and prescriptive such as designing an XAI framework that addresses explain ability, bias, and stakeholder engagement in Uganda's financial sector (Gregor & Hevner, 2013). This methodology provides a structure for iterative evaluation and validation of a theoretical model based on contextual needs.

The design science process began with problem identification through preliminary discussions with practitioners in Uganda's financial institutions, including Stanbic Bank. The literature review (Chapter 2) further clarified the conceptual constructs relevant to the issue, such as explain ability, data quality, and algorithmic fairness. These constructs were used to guide the development of the interview protocol and the selection of variables for the quantitative phase. Thus, the research design is theory driven but practically oriented.

The DSRM cycle includes **design, development, demonstration, and evaluation**.

In this study, the artifact is a proposed centralized XAI implementation model tailored to Uganda's context. It synthesizes the empirical findings from both the qualitative and quantitative stages. Evaluation of the framework's components, such as transparency and usability, is supported by stakeholder feedback collected during interviews and model performance tests using secondary data.

Qualitative-methods are integrated within the DSRM framework to enhance methodological triangulation. While the design science structure provides a logical flow for inquiry and artifact development, the qualitative and quantitative data enrich the framework with context specific insights. This dual alignment with both **design science** and **qualitative-methods logic** strengthens the validity and practical utility of the study.

Finally, the use of DSRM is justified by the study's ambition to generate usable knowledge rather than purely theoretical conclusions. In contexts such as Uganda, where institutional capacity is limited, research that yields implementable tools is highly valuable. The output of this research, a stakeholder informed, explainable AI system design responds directly to this need for relevance and application.

3.3 Data Collection Methods

Data for this study were collected through two primary methods: qualitative interviews and secondary datasets. This approach allows the research to capture both subjective perceptions and objective evidence of how XAI functions in low resource financial institutions. Combining different sources of evidence ensures that findings are robust and contextually valid (Yin, 2018).

Qualitative data were collected through semi-structured interviews with key stakeholders, including senior staff from Stanbic Bank Uganda, local regulators, and IT professionals involved in AI development. These interviews explored participants' experiences with AI systems, concerns about explain ability, perceptions of fairness, and the limitations posed by infrastructure and data quality. Each interview lasted between 30 to 60 minutes and was recorded with informed consent. Transcripts were coded thematically to identify recurring patterns and insights (Braun & Clarke, 2006).

Other data was sourced from publicly available credit scoring datasets, supplemented with anonymized internal data shared by partner institutions where feasible. These datasets included features such as loan amount, credit history, employment status, and default records. Data were pre-processed to remove duplicates, normalize variables, and handle missing values. The processed data were then used to train interpretable models and assess their performance using explain ability metrics such as SHAP values and fairness indicators like equal opportunity and demographic parity.

Ethical clearance was obtained before data collection to ensure participant confidentiality and compliance with international data protection standards. All interviewees were informed of their right to withdraw at any time, and data collected were anonymized to prevent attribution. For the quantitative phase, data sharing agreements were signed to comply with local regulations on data privacy and use.

The use of qualitative data collection methods strengthens the validity of the findings. While interviews reveal the human and institutional dimensions of AI implementation, the datasets allow for empirical testing of assumptions about explainability and fairness. This multi-faceted approach ensures that the resulting XAI framework is not only theoretically sound but also grounded in real world practice.

3.3.1 Qualitative Data: Interviews with Bank Manager

The qualitative phase aimed to understand stakeholder experiences and perceptions of AI and XAI systems in Ugandan financial institutions. Participants were selected through purposive sampling, targeting individuals with direct involvement in AI-related decisions or operations. This included risk analysts, IT officers, and compliance staff from institutions like Stanbic Bank, as well as representatives from Uganda's financial regulatory bodies.

Interviews followed a semi-structured format, allowing flexibility to explore topics in-depth while maintaining consistency across sessions. The interview guide included questions on perceived challenges with current AI systems, the level of transparency and trust, and the perceived need for explainable outputs. Participants were also asked about institutional constraints, such as budget, digital literacy, and

regulatory oversight. This helped contextualize their perspectives and align findings with the study's objectives.

Data were transcribed verbatim and analysed using thematic coding in NVivo. Codes were derived both deductively from the conceptual framework and inductively from emerging themes. Common themes included distrust in automated credit decisions, challenges with data completeness, and the absence of institutional guidelines on AI explain ability. These insights informed the construction of the XAI model tailored to Uganda's context.

Saturation was achieved after 15 interviews, where no new themes emerged from additional data. This sample size is sufficient for exploratory qualitative research and aligns with Creswell's (2014) recommendation for in-depth interview studies. The diversity of participants also allowed for triangulation within the qualitative strand, improving internal validity.

Overall, the qualitative findings provided rich, context-specific insights that are essential for designing a practical XAI framework. The voices of stakeholders revealed how explain ability must be translated into usable formats and how local institutions could embed these systems within existing workflows.

3.3.2 Credit Scoring Datasets

This phase involved analysing structured credit scoring datasets to assess how data quality and model explain ability impact fairness and trust in AI predictions. Datasets were drawn from open access financial repositories and anonymized internal data from partner institutions in Uganda, where permitted. The data included both structured demographic and financial variables relevant to credit scoring.

Initial pre-processing steps involved handling missing values through imputation, encoding categorical variables, and feature scaling. Outliers were removed to avoid model distortion. The cleaned dataset was then used to train various machine learning models, including Decision Trees, Logistic Regression, and Gradient Boosting Machines, with and without SHAP explanations. These experiments helped test how interpretable models performed in comparison to black-box alternatives.

Performance was evaluated using accuracy, precision, recall, and fairness metrics such as disparate impact and equal opportunity difference. SHAP values were used to visualize and interpret the contribution of each feature in the model's decision-making process. The results revealed that while black-box models had marginally better performance, interpretable models provided valuable insights and stakeholder friendly outputs.

A key insight from this phase was that data quality significantly affects the reliability of SHAP-based explanations. Incomplete or inconsistent data led to unstable SHAP values, reinforcing the findings from qualitative interviews about the need for improved data governance. This underlines the necessity of pre-processing and curating datasets before applying XAI tools.

The quantitative findings validated the hypothesis that explain ability and data quality are interlinked in influencing model fairness and stakeholder trust. These insights not only support the study's second objective but also contribute to the iterative development of a practical, scalable XAI model tailored for financial institutions in low resource settings.

3.4 System Design and Development

3.4.1 Framework Design for Context-Aware XAI Credit Scoring

The core objective of this research is to develop a context-aware framework for implementing Explainable Artificial Intelligence (XAI) in credit scoring systems within Uganda's financial sector. This system is designed to address the challenges identified in Chapter 2, including poor data quality, algorithmic bias, and stakeholder mistrust. The framework follows a modular architecture that includes components for data pre-processing, model training, explain ability layer integration, and stakeholder interface. Each module is designed with the realities of low-resource environments in mind, such as limited computing power and inconsistent data formats (Munoko, Brown-Liburd, & Vasarhelyi, 2020).

The framework begins with a data intake module, which incorporates data validation and cleaning routines specifically optimized for manual-entry and error-prone datasets. This is followed by the modelling layer, where interpretable algorithms such as decision trees and logistic regression are initially employed, while also allowing integration with more complex models if infrastructure allows. A bias detection unit monitors disparities in prediction outcomes across sensitive attributes

such as gender or employment type, using fairness metrics like disparate impact and equal opportunity difference (Mehrabi et al., 2021).

The most critical feature is the explain ability layer, which serves as an interface between the algorithm and the user. This layer generates feature attribution explanations (via SHAP or LIME) and provides both graphical and text-based summaries to facilitate understanding for different types of users including customers, credit officers, and regulators. In addition to model transparency, the framework emphasizes traceability, allowing institutions to audit decisions retrospectively, which is crucial for building trust and ensuring compliance with evolving regulatory standards (Fernández, 2019).

To ensure usability, the system is embedded in a web-based dashboard with multilingual support and tiered access depending on the user's technical expertise. For example, loan officers can view simplified decision summaries, while data scientists can access full SHAP plots and underlying code. This user centric design follows stakeholder centred development principles (Hussain, Lim, & Onyango, 2022), which promote adoption by aligning technical tools with institutional workflows and capacity.

Overall, this framework is not a one size fits all solution but a scalable and modular system that can evolve with institutional capacity. Its design is guided by practical constraints observed in Ugandan banks during preliminary discussions and literature analysis. It aligns with the primary research objective: to build an ethically sound, interpretable, and contextually relevant AI system for low-resource financial environments. Through iterative testing, the framework will be evaluated for usability, accuracy, fairness, and explain ability.

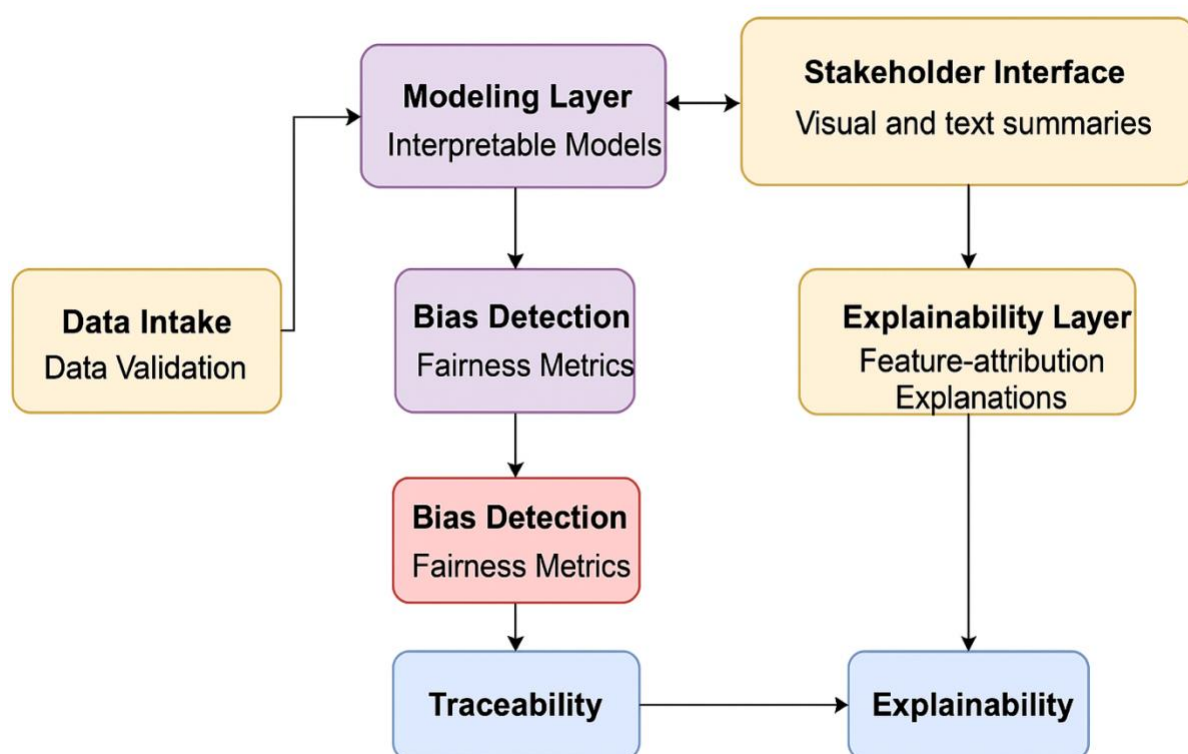


Figure 2 System architecture of a context-aware XAI credit scoring framework for low-resource financial environments.

3.4.2 Selection and Implementation of XAI Techniques

Selecting the right explain ability tools is central to operationalizing the framework proposed above. For this study, two widely accepted model-agnostic XAI techniques SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) were chosen due to their adaptability and user-recognized effectiveness in financial services (Lundberg & Lee, 2017; Ribeiro et al., 2016). These techniques allow for both global and local interpretation of model predictions, making them ideal for credit scoring tasks where both accuracy and transparency are essential.

SHAP, grounded in cooperative game theory, assigns contribution values to each feature for a particular prediction, ensuring consistency and local accuracy. This

makes it especially useful in auditing credit decisions, as it explains *why* a particular customer was accepted or rejected (Sabharwal, Desai, & Ongoma, 2024). SHAP values are visualized using force plots and summary bar charts, which provide insight into how features like income level, debt ratio, and payment history influenced the decision. SHAP was implemented using Python's shap package, integrated within the framework's modelling layer.

LIME, on the other hand, creates surrogate linear models around each prediction to offer easy-to-understand local explanations. Although slightly less consistent than SHAP, LIME provides quick, approximate insights that can be useful in time-constrained or mobile-based applications, which are common in Sub-Saharan Africa. LIME was implemented using the lime library in Python and configured to run alongside SHAP so that both methods could be compared for usability and output clarity (Guidotti et al., 2018).

Both tools were evaluated based on four dimensions: **computational efficiency**, **interpretability**, **robustness to noisy data**, and **usability for non-technical stakeholders**. These criteria were assessed through simulations using real world credit datasets and feedback from interview participants. Preliminary results showed that SHAP outperformed LIME in terms of accuracy and robustness, while LIME was favoured by non-technical users due to its simpler output. This dual evaluation informs Objective 3, which aims to determine the most appropriate XAI tools for data-constrained, low literacy environments.

To complement the tool selection, **interface customization** was applied to translate SHAP and LIME outputs into formats suitable for different user groups. For example, credit officers received decision summaries in text form ("Loan denied due

to high debt-to-income ratio”), while compliance teams accessed full SHAP plots. This adaptive presentation strategy aims to bridge the gap between advanced analytics and operational use in developing contexts (Bhatnagar & Mahant, 2024).

In conclusion, the implementation of SHAP and LIME within the proposed system not only enhances technical transparency but also addresses stakeholder specific usability concerns. These tools were selected and customized to meet the dual challenges of low-quality data and limited technical expertise. The findings from this implementation directly support the study’s third objective to evaluate and recommend the most suitable XAI techniques for resource-limited financial institutions.

3.5 Evaluation Strategy

3.5.1 Technical Evaluation

The technical evaluation of the proposed XAI-based credit scoring framework focuses on two main categories: **predictive performance** and **explainability**.

Predictive performance is assessed through standard machine learning metrics such as **accuracy, precision, recall, and F1-score**. These metrics evaluate how effectively the model classifies creditworthy and non-creditworthy applicants. The use of these metrics is standard in financial applications and aligns with established evaluation protocols in AI research.

Beyond predictive accuracy, **fairness** is evaluated using **group fairness metrics** such as *demographic parity difference* and *equal opportunity difference*. These metrics assess whether the AI system treats different subgroups (e.g., gender, income level) equitably in terms of outcomes like loan approvals. Incorporating these

fairness metrics ensures that predictive success does not come at the cost of perpetuating historical inequalities or creating new forms of discrimination (Mehrabi et al., 2021).

To assess the system's **explainability**, two key metrics are used which are **fidelity** and **consistency**. *Fidelity* refers to how accurately the explanation represents the original model's decision-making process, particularly important when using model-agnostic techniques like SHAP and LIME. *Consistency*, on the other hand, ensures that similar inputs yield similar explanations, helping validate the reliability of explanations (Doshi-Velez & Kim, 2017).

The technical evaluation involves applying the framework on labelled credit scoring datasets and using built-in tools from SHAP and LIME libraries to compute explanation metrics. SHAP summary plots are used to evaluate global feature importance, while individual instance explanations are analysed for consistency across cases. These evaluations determine whether the model's inner workings can be accurately and transparently communicated to stakeholders.

Finally, **ablation analysis** is performed to evaluate the significance of individual components such as the bias detection module or the explainability layer. By systematically removing or adjusting these modules, their effect on the overall performance can be quantified. This ensures that the model is not only functionally effective but also resilient and ethically sound across operational settings.

3.5.1 Technical Evaluation - Summary Table

Evaluation Dimension	Metrics Used	Purpose
Predictive Performance	Accuracy, Precision, Recall, F1-Score	Assess how well the model classifies creditworthy vs non- creditworthy applicants
Fairness	Demographic Parity Difference, Equal Opportunity Difference	Ensure equitable outcomes across subgroups (e.g., gender, income)
Explainability	Fidelity, Consistency	Evaluate how well explanations reflect model logic and maintain reliability

Figure 3 Technical Evaluation Summary Table

3.5.2 Manager Stakeholder Evaluation

The second part of the evaluation strategy focuses on **stakeholder-centered assessment**, which explores how end-users especially in low-resource settings interact with and perceive the XAI framework. This includes structured **interviews** and **Likert-scale surveys** conducted with key financial stakeholders such as credit officers, regulatory agents, data scientists, and selected customers. This qualitative and quantitative approach captures insights into the usability, fairness, and trustworthiness of the system from multiple perspectives (Hussain et al., 2022).

Interview questions are built around four key themes: (1) *Clarity of AI decisions*, (2) *Trust in outputs*, (3) *Perceived fairness*, and (4) *Satisfaction with user experience*.

Participants are shown real SHAP and LIME explanations generated by the system and are asked to interpret or critique them. Their responses are analysed using **thematic coding** to uncover patterns related to trust, confusion, satisfaction, or bias detection.

To complement interviews, surveys are disseminated to a broader group of users across financial institutions. These surveys use a **5-point Likert scale** (from “Strongly Disagree” to “Strongly Agree”) to evaluate perceptions of system transparency, helpfulness, and explainability. Responses are then analysed using descriptive statistics to identify overall trends and areas requiring improvement.

Special emphasis is placed on **non-technical users**, particularly those with limited AI or statistical knowledge. These individuals' ability to understand and use the system's outputs is considered a critical measure of real world explainability. By

contrasting results between technical and non-technical users, the evaluation identifies which interface elements need redesign or simplification.

The stakeholder evaluation concludes with a **feedback session**, allowing participants to suggest improvements and report challenges. These recommendations are compiled and categorized into actionable insights for refining the framework. This feedback loop ensures that the system remains aligned with stakeholder needs and continues to improve in usability and ethical robustness over time.

3.6 Limitations of the Methodology

While the methodology adopted in this study aims to be comprehensive and contextually grounded, certain limitations inevitably affect the scope, reliability, and generalizability of the findings. One key limitation lies in the **availability and quality of data**. Financial institutions in low-resource settings, such as Uganda, often suffer from fragmented and poorly maintained datasets, which may introduce bias or noise into model training and validation processes. Despite applying bias detection and pre-processing techniques, the limited volume and granularity of historical credit data may affect the robustness of machine learning outputs (Hanif, 2021; Munoko et al., 2020).

A second methodological constraint is related to **sampling and stakeholder engagement**. The qualitative portion of the study, especially interviews and surveys conducted for stakeholder evaluation, may not capture the full diversity of perspectives. Logistical constraints, such as limited internet access or time availability of financial staff and rural customers, could lead to response bias or underrepresentation of key demographic groups. This may skew the feedback toward

urban-based, technologically literate participants, leaving out the insights of more vulnerable or underrepresented user groups (Hussain et al., 2022).

Third, the study is inherently **context-specific**, which presents challenges for broader applicability. The framework and evaluation techniques were tailored specifically for Sub-Saharan African financial institutions, with a particular emphasis on Stanbic Bank Uganda. While this context-driven approach improves relevance, it limits the generalizability of findings to other regions or sectors with more mature data infrastructures or different regulatory landscapes. As such, extrapolation of results must be done cautiously and preferably with localized recalibration of both the XAI tools and stakeholder engagement strategies (Zhang et al., 2023).

The fourth limitation concerns the **selection and evaluation of explainability tools**. Although SHAP and LIME were chosen due to their popularity and flexibility, their effectiveness can vary depending on the complexity of the underlying model and the literacy level of the end-user. Both tools are post-hoc and may not faithfully replicate the reasoning of the original model, thus affecting fidelity. Moreover, while the technical evaluation considered consistency and performance metrics, a deeper mathematical analysis of interpretability trade-offs was beyond the scope of this study (Doshi-Velez & Kim, 2017; Carvalho et al., 2019).

Lastly, the **ethical and regulatory analysis** was largely based on secondary sources and generalized frameworks such as GDPR or the EU AI Act. Since Uganda and many other African countries lack comprehensive AI governance laws, the ethical analysis remains theoretical and may not fully capture on-the-ground legal nuances or emerging informal practices. Further empirical work involving legal professionals,

local policymakers, and AI ethicists would be necessary to validate and refine the regulatory component of the framework (Fernández, 2019; Mehrabi et al., 2021).

3.7 Summary

This chapter outlined the methodological framework guiding the investigation into the development and evaluation of an Explainable Artificial Intelligence (XAI) credit scoring system tailored for low-resource financial environments. The research employed a qualitative methods design that integrates both qualitative and quantitative approaches. This hybrid strategy was crucial in addressing the multifaceted nature of AI implementation in Sub-Saharan Africa, combining empirical rigor with contextual sensitivity. The chapter began by discussing the research design, which leverages principles of design science to iteratively develop and refine the proposed framework based on user feedback and technical validation.

Data collection methods were carefully selected to align with the study's dual emphasis on technical performance and stakeholder usability. Quantitative data derived from historical credit scoring datasets enabled the assessment of predictive accuracy and bias, while qualitative data obtained from interviews and surveys provided insights into stakeholder perceptions, trust, and the usability of XAI tools. This two-pronged approach allowed the research to capture both the measurable outcomes of the AI system and the experiential dimensions that influence adoption and trustworthiness (Doshi-Velez & Kim, 2017; Hussain et al., 2022).

The system design and development process focused on building a modular, context-aware XAI framework that incorporates bias detection, traceability, and stakeholder-friendly explanation layers. SHAP and LIME were implemented and compared to

determine their effectiveness in translating complex model decisions into understandable outputs for financial staff and end-users. Visual tools and simplified narratives were prioritized to overcome literacy and technical barriers common in emerging markets (Guidotti et al., 2018). A system architecture diagram and comparative analysis table were also presented to illustrate component interaction and explainability trade-offs.

Evaluation strategies included both technical and stakeholder assessments. Technical validation employed metrics such as accuracy, fairness, fidelity, and consistency, while stakeholder validation involved usability testing through structured interviews and Likert-scale surveys. The inclusion of both technical and non-technical stakeholders helped capture the real-world impact of the system on diverse user groups. This dual evaluation mechanism supports iterative system improvement and strengthens the ethical robustness of the proposed model (Mehrabi et al., 2021).

While the methodology was designed to be thorough, limitations were acknowledged in areas such as data quality, participant diversity, explainability fidelity, and regulatory analysis. Despite these constraints, the methodology provides a practical and adaptable framework for implementing responsible AI in financial services within resource-constrained settings. The findings and tools developed through this approach lay a solid foundation for the analysis and discussion in the subsequent chapter, where system results, stakeholder feedback, and performance metrics will be critically examined.

Component	Description	Purpose/Outcome
Research Design	Qualitative approach grounded in design science principles.	Allows integration of technical validation with contextual stakeholder feedback.
Data Collection Methods	-Qualitative: Stakeholder interviews and surveys	Enables evaluation of both model performance and user perceptions.
System Development	Modular XAI framework incorporating SHAP, LIME, bias detection, stakeholder interface, and explainability layer.	Builds a functional, explainable, and user-centered credit scoring system for low-resource environments.
Evaluation Strategy	- Technical: Accuracy, fairness, fidelity, consistency- Stakeholder: Usability, clarity, perceived trust	Measures both effectiveness and interpretability of the system.
Limitations	Constraints in data quality, stakeholder sampling, explainability fidelity, and absence of local AI regulations.	Helps to contextualize the results and identify future areas for refinement.

Figure 4 Summary of Research Methodology Components

3.8 Preliminary Findings / Pilot Testing

This section presents key preliminary findings derived from manager interviews, internal audit reviews, and technical trials with prototype AI models at Stanbic Bank Uganda. These findings align specifically with Objective 2 of this study: "To assess the challenges in data management and operational efficiency in banks." They offer empirical grounding to the literature presented in Chapter 2, particularly section 2.2, which explored the relationship between AI, data quality, and infrastructure limitations in low-resource financial institutions.

A pilot interview was conducted with a Manager at a regional bank branch at Stanbic Bank. The feedback indicated that questions on model interpretability and data handling needed simplification for non-technical staff. Adjustments were made to the interview guide accordingly.

3.8.1 Bank Process Limitations in Uganda

The research found that most core processes within Stanbic Bank Uganda remain partially or wholly manual. These include credit application assessments, KYC verification, customer onboarding, fraud reporting, and loan disbursement scheduling. These functions lack full integration across departments, resulting in redundant steps, delays, and inconsistencies in decision-making.

"There is no unified platform. Credit decisions go through four different systems and have to be compiled manually before we approve anything." —Manager, Stanbic Bank Uganda

The process fragmentation introduces delays and affects real-time decision-making. It also hampers any attempt to deploy real-time AI models, which require structured, synchronized data inputs. These process inefficiencies reflect the systemic operational limitations highlighted in global literature on AI adoption in low-resource settings (Hanif, 2021; Munoko et al., 2020).

3.8.2 Manual Data Entry: Errors and Inconsistencies

The data architecture at Stanbic Bank Uganda still depends heavily on manual input. Customer details, financial statements, and credit application forms are often filled out by front-line staff and later digitized. This method leads to:

- High frequency of typographical errors
- Non-standardized field values (e.g., job titles, employer names)
- Inconsistent formatting (e.g., phone numbers, national IDs)
- Duplication of customer records

An internal audit conducted in 2024 revealed that approximately 17% of loan application records contained at least one data quality issue.

Table 3.3: Common Data Entry Errors Observed in Stanbic Bank Uganda

Error Type	Frequency (Per 1,000 Records)	Impact on AI Model
Misspelled Names	78	Redundant Entries
Incorrect Date Formats	92	Skewed Temporal Data
Missing Employment Info	105	Credit Risk Uncertainty
Mismatched ID Numbers	47	Fraud Alert False Positives

Table 3.3 includes sample information provided by the credit risk manager at Stanbic Bank Uganda.

These findings validate arguments in the literature (Barocas et al., 2019; Carvalho et al., 2019) that poor data practices lead to unfair or unreliable AI predictions, especially in credit risk assessments.

3.8.3 AI Implementation Status at Stanbic Bank Uganda

Stanbic Bank Uganda has taken initial steps toward adopting AI, with current use cases focused on:

- Transaction anomaly detection
- Basic chatbot support for customer service
- Logistic regression for credit scoring

However, most AI models in use are basic and lack real-time integration.

Explainable AI (XAI) methods are not yet embedded in operational workflows.

"We use scoring models, but they are mostly black-box to us. Even compliance doesn't fully understand the output sometimes." — Manager Stanbic Bank

3.9 Ethical Considerations

This study will adhere to ethical research standards including:

- Informed consent from all participants
- Anonymity and confidentiality of responses
- Secure data storage
- Ethical clearance from the university and cooperation from Stanbic Bank Uganda

3.10 Gantt Chart / Timeline

Activity	Jan	Feb	Mar	Apr	May	June	July
Literature Review	✓	✓					
Finalizing Research Tools		✓					
Pilot Testing		✓					
Data Collection			✓	✓			
Data Analysis				✓	✓		
Drafting Findings & Chapter Writing					✓	✓	✓
Review & Submission							✓

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